II. Cluster Analysis

- Cluster Analysis Basics
- Hierarchical Cluster Analysis
- Iterative Cluster Analysis
- Density-Based Cluster Analysis
- Cluster Evaluation
- Constrained Cluster Analysis
Hierarchical Cluster Analysis

Merging Principles

- **Hierarchical**
  - Agglomerative
    - Single link, group average
  - Divisive

- **Iterative**
  - Exemplar-based
  - Exchange-based

- **Density-based**
  - Point-density-based
    - DBSCAN
  - Attraction-based
    - Kerninghan-Lin

- **Meta-search-controlled**
  - Gradient-based
    - Simulated annealing
  - Competitive
    - Evolutionary strategies

- **Stochastic**
  - Gaussian mixtures

Cluster analysis
Hierarchical Cluster Analysis
Hierarchical Agglomerative Algorithm

Input: \( G = \langle V, E, w \rangle \). Weighted graph.
\( d_C \). Distance measure for two clusters.

Output: \( T = \langle V_T, E_T \rangle \). Cluster hierarchy or dendrogram.

1. \( C = \{\{v\} | v \in V\} \) // initial clustering

2.

3. WHILE \( |C| > 1 \) DO

4. \( \text{update\_distance\_matrix}(C, G, d_C) \)

5. \( \{C, C'\} = \arg\min_{\{C_i, C_j\} \in C: C_i \neq C_j} d_C(C_i, C_j) \) // find closest clusters

6. \( C = (C \setminus \{C, C'\}) \cup \{C \cup C'\} \) // merge clusters

7.

8. ENDDO

9. RETURN\((T)\)

Compare the above algorithm to the hierarchical divisive algorithm.
Hierarchical Cluster Analysis
Hierarchical Agglomerative Algorithm

Input: \( G = \langle V, E, w \rangle \). Weighted graph.
\( d_C \). Distance measure for two clusters.

Output: \( T = \langle V_T, E_T \rangle \). Cluster hierarchy or dendrogram.

1. \( C = \{\{v\} \mid v \in V\} \) // initial clustering
2. \( V_T = \{v_C \mid C \in C\}, \ E_T = \emptyset \) // initial dendrogram
3. \textbf{WHILE} \( |C| > 1 \) \textbf{DO}
4. \( \text{update\_distance\_matrix}(C, G, d_C) \)
5. \( \{C, C'\} = \underset{\{C_i, C_j\} \in C: C_i \neq C_j}{\text{argmin}} \ d_C(C_i, C_j) \) // find closest clusters
6. \( C = (C \setminus \{C, C'\}) \cup \{C \cup C'\} \) // merge clusters
7. \( V_T = V_T \cup \{v_C, v_{C'}\}, \ E_T = E_T \cup \{\{v_C, v_{C'}, v_C\}, \{v_C, v_{C'}, v_{C'}\}\} \) // dendrogram
8. \textbf{ENDDO}
9. \textbf{RETURN}(T)

Compare the above algorithm to the hierarchical divisive algorithm.
Hierarchical Cluster Analysis

Single Link: Cluster Distance Measure $d_C = \text{Nearest Neighbor}$
Hierarchical Cluster Analysis

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Hierarchical Cluster Analysis

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Hierarchical Cluster Analysis

Single Link: Cluster Distance Measure $d_C = \text{Nearest Neighbor}$
Hierarchical Cluster Analysis

Distance Re-Computation after each Merging Step

\[
\begin{array}{cccc}
C_1 & C_2 & \ldots & C_n \\
C_1 & 0 & d_C(C_1, C_2) & \ldots & d_C(C_1, C_n) \\
C_2 & - & 0 & \ldots & d_C(C_2, C_n) \\
\vdots & & & \ddots & \vdots \\
C_n & - & - & \ldots & 0 \\
\end{array}
\]

\[
\begin{array}{cccc}
x_1 & x_2 & \ldots & x_n \\
x_1 & 0 & d(x_1, x_2) & \ldots & d(x_1, x_n) \\
x_2 & - & 0 & \ldots & d(x_2, x_n) \\
\vdots & & & \ddots & \vdots \\
x_n & - & - & \ldots & 0 \\
\end{array}
\]

\[\equiv\]
Hierarchical Cluster Analysis
Distance Re-Computation after each Merging Step

<table>
<thead>
<tr>
<th></th>
<th>$C_1$</th>
<th>$C_2$</th>
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$t = 0$

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$\equiv$
Hierarchical Cluster Analysis

Distance Re-Computation after each Merging Step

\[ t = 0 \]

\[
\begin{array}{cccc}
C_1 & C_2 & \ldots & C_n \\
C_1 & 0 & d_C(C_1, C_2) & \ldots & d_C(C_1, C_n) \\
C_2 & - & 0 & \ldots & d_C(C_2, C_n) \\
\vdots & & & \ddots & \vdots \\
C_n & - & - & \ldots & 0 \\
\end{array}
\]

\[ t = i \]

\[
\begin{array}{cccc}
C_{i_1} & C_{i_2} & \ldots & C_{i_{n-i}} \\
C_{i_1} & 0 & d_C(C_1, C_{i_2}) & \ldots & d_C(C_{i_1}, C_{i_{n-i}}) \\
C_{i_2} & - & 0 & \ldots & d_C(C_{i_2}, C_{i_{n-i}}) \\
\vdots & & & \ddots & \vdots \\
C_{i_{n-i}} & - & - & \ldots & 0 \\
\end{array}
\]

\[ x_1 \quad x_2 \quad \ldots \quad x_n \]

\[
\begin{array}{cccc}
x_1 & 0 & d(x_1, x_2) & \ldots & d(x_1, x_n) \\
x_2 & - & 0 & \ldots & d(x_2, x_n) \\
\vdots & & & \ddots & \vdots \\
x_n & - & - & \ldots & 0 \\
\end{array}
\]
Hierarchical Cluster Analysis
Distance Re-Computation after each Merging Step

<table>
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<th>$t = 0$</th>
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<th>$C_2$</th>
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<th>$C_n$</th>
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<tr>
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<td>...</td>
<td>$d_C(C_2, C_n)$</td>
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<td>...</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$C_n$</td>
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<table>
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</table>

$\equiv$

<table>
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<tr>
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<th>$x_2$</th>
<th>...</th>
<th>$x_n$</th>
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</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>0</td>
<td>$d(x_1, x_2)$</td>
<td>...</td>
</tr>
<tr>
<td>$x_2$</td>
<td>-</td>
<td>0</td>
<td>...</td>
</tr>
<tr>
<td>...</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$x_n$</td>
<td>-</td>
<td>-</td>
<td>...</td>
</tr>
</tbody>
</table>
Hierarchical Cluster Analysis
Distance Measures of Hierarchical Agglomerative Algorithms

<table>
<thead>
<tr>
<th>Distance Measure</th>
<th>Formula</th>
<th>Algorithm</th>
</tr>
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<tbody>
<tr>
<td>Single Link (Nearest Neighbor)</td>
<td>$d_C(C, C') = \min_{u \in C, v \in C'} d(u, v)$</td>
<td><strong>single link</strong></td>
</tr>
<tr>
<td>Complete Link (Furthest / Farthest Neighbor)</td>
<td>$d_C(C, C') = \max_{u \in C, v \in C'} d(u, v)$</td>
<td><strong>complete link</strong></td>
</tr>
<tr>
<td>Group Average Link</td>
<td>$d_C(C, C') = \frac{1}{</td>
<td>C</td>
</tr>
<tr>
<td>Ward Criterion (Variance)</td>
<td>$d_C(C, C') = \sqrt{\frac{2 \cdot</td>
<td>C</td>
</tr>
</tbody>
</table>

How the distance measures are employed:

- **hierarchical agglomerative algorithm**
- **hierarchical divisive algorithm**
Hierarchical Cluster Analysis

Ward Criterion

Ward is a variance criterion. It is the (double) increase of the error sum of squares, \( ESS \), in the new cluster that results from merging the two clusters \( C \) and \( C' \).

Derivation:

\[
ESS(C') = \sum_{u \in C} ||\bar{u} - u||^2
\]
Hierarchical Cluster Analysis

Ward Criterion

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$$ESS(C') = \sum_{u \in C'} \|\bar{u} - u\|^2 = \sum_{u \in C'} \left(\|\bar{u}\|^2 - 2 \cdot \langle u, \bar{u} \rangle + \|u\|^2\right)$$

$\bar{u}$ and $\bar{v}$ denote the mean of the points $u \in C$ and $v \in C'$ respectively.
Hierarchical Cluster Analysis

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\]

\[
= |C'| \cdot \|\bar{u}\|^2 - 2|C'| \cdot \|\bar{u}\|^2 + \sum_{u \in C'} \|u\|^2
\]

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\[
ESS(C') = \sum_{u \in C'} ||\bar{u} - u||^2 = \sum_{u \in C'} \left( ||\bar{u}||^2 - 2 \cdot \langle u, \bar{u} \rangle + ||u||^2 \right)
\]

\[
= |C'| \cdot ||\bar{u}||^2 - 2|C'| \cdot ||\bar{u}||^2 + \sum_{u \in C'} ||u||^2 = \sum_{u \in C'} ||u||^2 - |C'| \cdot ||\bar{u}||^2
\]

\( \bar{u} \) and \( \bar{v} \) denote the mean of the points \( u \in C \) and \( v \in C' \) respectively.
Hierarchical Cluster Analysis

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$$= |C| \cdot ||\bar{u}||^2 - 2|C| \cdot ||\bar{u}||^2 + \sum_{u \in C'} ||u||^2 = \sum_{u \in C'} ||u||^2 - |C| \cdot ||\bar{u}||^2$$

$$ESS(C') = \sum_{v \in C'} ||v||^2 - |C'| \cdot ||\bar{v}||^2$$
Hierarchical Cluster Analysis

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$$\text{ESS}(C') = \sum_{v \in C'} ||v||^2 - |C'| \cdot ||\bar{v}||^2$$

$$\text{ESS}(C \cup C') = \sum_{w \in (C \cup C')} ||w||^2 - |C \cup C'| \cdot ||\bar{w}||^2$$,

where $\bar{w} = \frac{|C| \cdot \bar{u} + |C'| \cdot \bar{v}}{|C| + |C'|}$
Hierarchical Cluster Analysis

Ward Criterion

Ward is a variance criterion. It is the (double) increase of the error sum of squares, $ESS$, in the new cluster that results from merging the two clusters $C$ and $C'$. Derivation:

$$ESS(C') = \sum_{u \in C} ||\bar{u} - u||^2 = \sum_{u \in C} \left( ||\bar{u}||^2 - 2 \cdot \langle u, \bar{u} \rangle + ||u||^2 \right)$$

$$= |C| \cdot ||\bar{u}||^2 - 2|C| \cdot ||\bar{u}||^2 + \sum_{u \in C} ||u||^2 = \sum_{u \in C} ||u||^2 - |C| \cdot ||\bar{u}||^2$$

$$ESS(C') = \sum_{v \in C'} ||v||^2 - |C'| \cdot ||\bar{v}||^2$$

$$ESS(C \cup C') = \sum_{w \in (C \cup C')} ||w||^2 - |C \cup C'| \cdot ||\bar{w}||^2, \quad \text{where} \quad \bar{w} = \frac{|C| \cdot \bar{u} + |C'| \cdot \bar{v}}{|C| + |C'|}$$

$$ESS(C \cup C') - ESS(C) - ESS(C') = \ldots = \frac{|C| \cdot |C'|}{|C| + |C'|} \cdot ||\bar{u} - \bar{v}||^2$$

$\bar{u}$ and $\bar{v}$ denote the mean of the points $u \in C$ and $v \in C'$ respectively.
Hierarchical Cluster Analysis
Update Formula for Cluster Distances

After merging two clusters $C$ and $C'$ into a single new cluster, the resulting distances to other the clusters $C_i$, $d_C(C \cup C', C_i)$, have to be computed.

By exploiting the already computed distances, the Lance-Williams update formula provides an efficient means (linear time in the current number of clusters) to obtain the desired new distances:

$$d_C(C \cup C', C_i) = \alpha \cdot d_C(C, C_i) + \beta \cdot d_C(C', C_i) + \gamma \cdot d_C(C, C') + \delta \cdot |d_C(C, C_i) - d_C(C', C_i)|$$

The constants $\alpha, \beta, \gamma, \delta$ are specific for single link, complete link, average link, and the ward criterion. The constants are derived on the basis of the respective computation rules for $d_C$. 
Hierarchical Cluster Analysis
Update Formula for Cluster Distances (continued)

After merging two clusters $C$ and $C'$ into a single new cluster, the resulting distances to other the clusters $C_i$, $d_C(C \cup C', C_i)$, have to be computed.

Derivation of the update formula for single link, where $d_C = \text{nearest neighbor}$:

$$d_C(C \cup C', C_i) = \min_{u \in (C \cup C')} d(u, v) \quad \text{[distance measure]}$$
Hierarchical Cluster Analysis
Update Formula for Cluster Distances (continued)

After merging two clusters \( C \) and \( C' \) into a single new cluster, the resulting distances to other the clusters \( C_i, \; d_C(C \cup C', C_i) \), have to be computed.

Derivation of the update formula for single link, where \( d_C = \) nearest neighbor:

\[
d_C(C \cup C', C_i) = \min_{u \in (C \cup C')} d(u, v) \quad \text{[distance measure]}
\]

\[
= \min\{d_C(C, C_i), \; d_C(C', C_i)\}
\]
Hierarchical Cluster Analysis

Update Formula for Cluster Distances (continued)

After merging two clusters $C$ and $C'$ into a single new cluster, the resulting distances to other the clusters $C_i$, $d_C(C \cup C', C_i)$, have to be computed.

Derivation of the update formula for single link, where $d_C = \text{nearest neighbor}$:

$$d_C(C \cup C', C_i) = \min_{u \in (C \cup C')} \min_{v \in C_i} d(u, v) \quad \text{[distance measure]}$$

$$= \min\{d_C(C, C_i), d_C(C', C_i)\}$$

$$= 0.5 \cdot (d_C(C, C_i) + d_C(C', C_i)) - 0.5 \cdot |d_C(C, C_i) - d_C(C', C_i)|$$
Hierarchical Cluster Analysis
Update Formula for Cluster Distances (continued)

After merging two clusters \( C \) and \( C' \) into a single new cluster, the **resulting distances** to other the clusters \( C_i \), \( d_C(C \cup C', C_i) \), have to be computed.

Derivation of the update formula for single link, where \( d_C = \) nearest neighbor:

\[
d_C(C \cup C', C_i) = \min_{u \in (C \cup C')} \min_{v \in C_i} d(u, v) \quad \text{[distance measure]}
\]

\[
= \min\{d_C(C, C_i), d_C(C', C_i)\}
\]

\[
= 0.5 \cdot (d_C(C, C_i) + d_C(C', C_i)) - 0.5 \cdot |d_C(C, C_i) - d_C(C', C_i)|
\]

\[
= 0.5 \cdot d_C(C, C_i) + 0.5 \cdot d_C(C', C_i) + (-0.5) \cdot |d_C(C, C_i) - d_C(C', C_i)|
\]

\[
\downarrow \quad \downarrow \quad \downarrow \\
\alpha \quad \beta \quad \delta
\]
Remarks:

- Link-based algorithms can be used with arbitrary measures for distances and similarities.
- Single link can be operationalized straightforwardly with a minimum spanning tree algorithm such as Prim’s algorithm. [Wikipedia]
- Variance-based approaches presume interval-based measurement scales for all features.
- The uniform pseudo code structure of the hierarchical agglomerative algorithm reveals the close relation of the different cluster analysis variants. However, this structural similarity must be regarded with caution: the features’ measurement scales along with the point distance computation rule, $d(u, v)$, determine the basic merging characteristics of a cluster analysis algorithm.
- Basic idea of the Lance-Williams update formula: instead of analyzing after a merging step all members (points) of two clusters again, the formula exploits the cluster distances that were already computed in the preceding iteration before the merger.

How large is the runtime improvement compared to a naive approach that exploits only the distance information in $G = \langle V, E, w \rangle$?
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = $ Nearest Neighbor)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = \text{Nearest Neighbor}$)
Hierarchical Cluster Analysis
Chaining Problem of Single Link \((d_C = \text{Nearest Neighbor})\)
Hierarchical Cluster Analysis
Chaining Problem of Single Link ($d_C = \text{Nearest Neighbor}$)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_c = \text{Nearest Neighbor}$)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = \text{Nearest Neighbor}$)
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Chaining Problem of Single Link ($d_C = \text{Nearest Neighbor}$)
Hierarchical Cluster Analysis

Chaining Problem of Single Link \((d_C = \text{Nearest Neighbor})\)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_c = \text{Nearest Neighbor}$)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = $ Nearest Neighbor)
Remarks:

- A $k$-nearest-neighbor variant may help to mitigate the chaining problem.
- A $k$-nearest-neighbor variant will prefer larger clusters as agglomeration candidates: larger clusters contain more points and hence are more likely to become a nearest neighbor than smaller clusters.
Hierarchical Cluster Analysis
Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)
Hierarchical Cluster Analysis
Chaining Problem of Single Link ($d_c = k$-Nearest-Neighbor)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_c = k$-Nearest-Neighbor)
Hierarchical Cluster Analysis
Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)
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Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)
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Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)

In certain situations $k$-nearest-neighbor can fail as well.
Hierarchical Cluster Analysis
Chaining Problem of Single Link \((d_C = k\)-Nearest-Neighbor)\)

In certain situations \(k\)-nearest-neighbor can fail as well.
Hierarchical Cluster Analysis
Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)

In certain situations $k$-nearest-neighbor can fail as well.
Hierarchical Cluster Analysis

Chaining Problem of Single Link ($d_C = k$-Nearest-Neighbor)

In certain situations $k$-nearest-neighbor can fail as well.
Particular pattern recognition tasks or the detection of hyperspheres requires to deal with nested clusters.
Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = $ Furthest Neighbor)
Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = $ Furthest Neighbor)

[characteristics]
Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = \text{Furthest Neighbor}$)
Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = $ Furthest Neighbor)
Hierarchical Cluster Analysis
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Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = $ Furthest Neighbor)
Hierarchical Cluster Analysis

Nesting Problem of Complete Link ($d_C = $ Furthest Neighbor)

Reality

Wish
Hierarchical Cluster Analysis

Characteristics of Hierarchical Agglomerative Algorithms

Geometrical characteristics:

<table>
<thead>
<tr>
<th>characteristic</th>
<th>single link</th>
<th>complete link</th>
<th>average link</th>
<th>Ward criterion</th>
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<td>conservative:</td>
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<td>medium</td>
<td>medium</td>
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<td>low</td>
<td>low</td>
<td>low</td>
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Hierarchical Cluster Analysis
Characteristics of Hierarchical Agglomerative Algorithms

<table>
<thead>
<tr>
<th>Geometrical characteristics:</th>
<th>single link</th>
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<th>average link</th>
<th>Ward criterion</th>
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| Data-related characteristics: |           |               |              |                |
| noisy data                   | susceptible| susceptible   | unaffected   | unaffected     |
| feature transformation       | invariant  | invariant     | –            | –              |
### Hierarchical Cluster Analysis

#### Characteristics of Hierarchical Agglomerative Algorithms

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#### Characteristics of the cluster distance measure $d_c$:

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<th>order dependence</th>
<th>consistency</th>
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<tr>
<td></td>
<td>✓</td>
<td>✓</td>
<td>→ 0</td>
</tr>
<tr>
<td></td>
<td>✓</td>
<td>✓</td>
<td>→ ∞</td>
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Remarks:

- The previous table also shows the usage frequency of the algorithms: single link and complete link are the most popular hierarchical agglomerative algorithms.  
  [Jain/Murty/Flynn 1999]

- The Ward criterion has been well-proven for cluster of equal sizes.

- Average link prefers spherical cluster forms, but it will also be able to detect “potato-shaped” clusters.  [Kaufman/Rousseeuw 1990, p.47]

- Chaining will also happen when the median distance is employed.

- The median distance and is not a monotonic cluster distance measure.  
  [Kaufman/Rousseeuw 1990, pp. 205+240]
Hierarchical Cluster Analysis

Hierarchical Divisive Algorithm

Input: \[ G = \langle V, E, w \rangle \]. Weighted graph.
\[ d_C \]. Distance measure for two clusters.

Output: \[ T = \langle V_T, E_T \rangle \]. Cluster hierarchy or dendrogram.

1. \[ C = \{V\} \] // initial clustering
2. 
3. WHILE \[ \exists C_x : (C_x \in C \land |C_x| > 1) \] DO
4. \[ \{C, C'\} = \operatorname{arg\,max}_{\{C_i, C_j\} : C_i \cup C_j = C_x \land C_i \cap C_j = \emptyset} d_C(C_i, C_j) \] // find farthest cluster candidates
5. \[ C = (C \setminus \{C_x\}) \cup \{C, C'\} \] // update clustering
6. 
7. ENDDO
8. RETURN(\[ T \])

Compare the above algorithm to the hierarchical agglomerative algorithm.
Hierarchical Cluster Analysis

Hierarchical Divisive Algorithm

Input: \( G = \langle V, E, w \rangle \). Weighted graph.
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Output: \( T = \langle V_T, E_T \rangle \). Cluster hierarchy or dendrogram.

1. \( C = \{V\} \) // initial clustering
2. \( V_T = \{v_C | C \in C\}, \ E_T = \emptyset \) // initial dendrogram
3. **WHILE** \( \exists C_x : (C_x \in C \land |C_x| > 1) \) **DO**

4. \( \{C, C'\} = \arg\max_{\{C_i, C_j\}} d_C(C_i, C_j) \) // find farthest cluster candidates

5. \( C = (C \setminus \{C_x\}) \cup \{C, C'\} \) // update clustering

6. \( V_T = V_T \cup \{v_C, v_C'\}, \ E_T = E_T \cup \{(v_{C_x}, v_C), (v_{C_x}, v_C')\} \) // dendrogram

7. **ENDDO**

8. **RETURN**(T)

Compare the above algorithm to the **hierarchical agglomerative algorithm**.
Remarks:

- The cluster distance measure $d_C$ can be chosen as with the hierarchical agglomerative algorithms. However, the worst-case complexity is exponential instead of quadratic.

- Hierarchical divisive algorithm are often designed according to the *monothetic* paradigm: within each decision step only a single feature is considered.

  The monothetic paradigm is particularly useful for features with ordinal and interval-based measurement scales: instead of considering all possible partitionings, a set of feature vectors is split with regard to a location parameter such as a feature’s median or a feature’s mean.

- In contrast to hierarchical agglomerative algorithms, a hierarchical divisive algorithm cannot repair a “wrong” partitioning from a previous iteration.

- A powerful hierarchical divisive algorithm is based on the *cut weight* of a graph:

$$sim_C(C, C') = \sum_{e \in \text{cut}\{C, C'\}} w(e) \quad \text{or} \quad d_C(C, C') = \frac{1}{sim_C(C, C')}$$
Hierarchical Cluster Analysis

MinCut

**Definition 4 (Cut, Minimum Cut)**

Let $G = \langle V, E, w \rangle$ be a graph with a non-negative weight function $w$. Let $U \subset V$ be a non-empty subset of the node set $V$ and let $\bar{U}$ be defined as $\bar{U} = V \setminus U$. Then the cut between $U$ and $\bar{U}$ is defined as follows:

$$\text{cut}(\{U, \bar{U}\}) = \{\{u, v\} \mid \{u, v\} \in E, u \in U, v \in \bar{U}\}$$
Hierarchical Cluster Analysis

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The weight (or the capacity) of $\cut(U, \bar{U})$ is defined as follows:

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Hierarchical Cluster Analysis

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The weight (or the capacity) of $\text{cut}(\{U, \bar{U}\})$ is defined as follows:

$$w(\{U, \bar{U}\}) = \sum_{e \in \text{cut}(\{U, \bar{U}\})} w(e)$$

$\text{cut}(\{U, \bar{U}\})$ is called minimum capacity cut of $G$, iff for all splittings $\{W, \bar{W}\}$, $W, \bar{W} \neq \emptyset$ holds:

$$w(\{U, \bar{U}\}) \leq w(\{W, \bar{W}\})$$
Hierarchical Cluster Analysis

MinCut
Hierarchical Cluster Analysis

MinCut
Hierarchical Cluster Analysis
MinCut
Hierarchical Cluster Analysis

MinCut
Remarks:

- Each partitioning requires the computation of a minimum capacity cut. Note that no node is labeled as source or sink.
- The runtime complexity of the best known algorithm for the computation of a minimum capacity cut is in \( O(|V| \cdot |E| + |V|^2 \cdot \log |V|) \). [Nagamochi/Ono/Ibaraki 1994]
- \(|V| - 1\) computations of a minimum capacity cut are necessary to obtain a complete partitioning (= one node per cluster).
- The effort for the computation of a minimum \( s-t \)-cut, i.e., a cut that considers a source \( s \) and a sink \( t \), is in \( O(|V|^2 \log(|E|)) \).
- The effort for the computation of a balanced minimum cut (\( k \)-way, \( k \geq 2 \)) is NP complete.
- In the literature on the subject, MinCut is not classified as a hierarchical algorithm but treated as a special approach.
Hierarchical Cluster Analysis

Splitting Problem of MinCut
Hierarchical Cluster Analysis
Splitting Problem of MinCut

Wish
Hierarchical Cluster Analysis

Splitting Problem of MinCut

Solution: Normalization of the cut capacity with regard to the node number.
Hierarchical Cluster Analysis

Splitting Problem of MinCut

Normalized cut capacity:

\[
\bar{w}(\{U, \bar{U}\}) = \frac{w(\{U, \bar{U}\})}{w(\{U, V\})} + \frac{w(\{U, \bar{U}\})}{w(\{U, V\})}
\]

Illustration of \(\bar{w}\):

\[
cut(\{U, \bar{U}\}) = \{\{u, v\} | \{u, v\} \in E, u \in U, v \in \bar{U}\}, \quad w(\{U, \bar{U}\}) = \sum_{e \in cut(\{U, \bar{U}\})} w(e)
\]
Hierarchical Cluster Analysis

Splitting Problem of MinCut

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\[ w(\{U, \bar{U}\}) = 2 \]

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Hierarchical Cluster Analysis

Splitting Problem of MinCut

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Hierarchical Cluster Analysis

Splitting Problem of MinCut

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Illustration of \(\overline{w}\):

\[
w(\{\bar{U}, V\}) = 30
\]

\[
cut(\{U, \bar{U}\}) = \{\{u, v\} \mid \{u, v\} \in E, u \in U, v \in \bar{U}\}, \quad w(\{U, \bar{U}\}) = \sum_{e \in cut(\{U, \bar{U}\})} w(e)
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Hierarchical Cluster Analysis

Splitting Problem of MinCut

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\]

Illustration of \(\overline{w}\):

\[
\overline{w}(\{U, \overline{U}\}) = \frac{\frac{2}{10}}{\frac{2}{16}} + \frac{\frac{2}{22}}{\frac{2}{16}} \approx 0.29
\]
\[
\overline{w}(\{U, \overline{U}\}) = \frac{\frac{2}{16}}{\frac{2}{16}} + \frac{\frac{2}{10}}{\frac{2}{22}} \approx 0.25
\]
\[
\overline{w}(\{U, \overline{U}\}) = \frac{\frac{2}{2}}{\frac{2}{30}} + \frac{\frac{2}{10}}{\frac{2}{22}} \approx 1.07
\]

\[
cut(\{U, \overline{U}\}) = \{\{u, v\} \mid \{u, v\} \in E, u \in U, v \in \overline{U}\}, \quad w(\{U, \overline{U}\}) = \sum_{e \in cut(\{U, \overline{U}\})} w(e)
\]
Remarks:

- The computation of a minimum cut of normalized cut capacity is NP complete.
- Efficient approximations for the computation of $\overline{w}(\{U, \bar{U}\})$ have been developed and used for image segmentation and gene expression cluster analysis. [Shi/Malik 2000]
Hierarchical Cluster Analysis
Combination of Hierarchical Algorithms

The system Chameleon combines graph thinning, graph partitioning, and a hierarchical cluster analysis [Karypis/Han/Kumar 2000]:
Hierarchical Cluster Analysis
Combination of Hierarchical Algorithms

The system Chameleon combines graph thinning, graph partitioning, and a hierarchical cluster analysis [Karypis/Han/Kumar 2000]:

The cluster distance $d_C(C, C')$ is defined as

$$d_C = \frac{1}{R_I(C, C') \cdot (R_C(C, C'))^\alpha}$$
The hyperparameter $\alpha$ in $d_C$ is taskdepending and has to be determined by the user (via trial and error).